HW3

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5/18/2022

```
knitr::opts_chunk$set(echo = TRUE)
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.1.3

## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.1.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
library(arrow)
```

```
## Warning: package 'arrow' was built under R version 4.1.3

##
## Attaching package: 'arrow'

## The following object is masked from 'package:lubridate':
##
##     duration

## The following object is masked from 'package:utils':
##
##     timestamp
```

```
library(readr)
library(gender)
```

```
## Warning: package 'gender' was built under R version 4.1.3
```

```
library(wru)
```

```
## Warning: package 'wru' was built under R version 4.1.3
```

```
library(lubridate)
library(ggplot2)
library(igraph)
```

```
## Warning: package 'igraph' was built under R version 4.1.3
```

```
##
## Attaching package: 'igraph'
```

```
## The following objects are masked from 'package:lubridate':
##
##     %--%, union
```

```
## The following objects are masked from 'package:dplyr':
##
##     as_data_frame, groups, union
```

```
## The following objects are masked from 'package:purrr':
##
##     compose, simplify
```

```
## The following object is masked from 'package:tidyr':
##
##     crossing
```

```
## The following object is masked from 'package:tibble':
##
##     as_data_frame
```

```
## The following objects are masked from 'package:stats':
##
##     decompose, spectrum
```

```
## The following object is masked from 'package:base':
##
##     union
```

```
library(ggraph)
```

```
## Warning: package 'ggraph' was built under R version 4.1.3
```

```
library(tidygraph)
```

```
## Warning: package 'tidygraph' was built under R version 4.1.3

##
## Attaching package: 'tidygraph'

## The following object is masked from 'package:igraph':
##
##     groups

## The following object is masked from 'package:stats':
##
##     filter
```

Load data

Load the following data: + applications from `app_data_sample.parquet` + edges from `edges_sample.csv`

```
data_path <- "C:/Users/admin/Documents/R projects/2022-ona-assignments/"
applications <- read_parquet(paste0(data_path,"app_data_sample.parquet"))
edges <- read_csv(paste0(data_path,"edges_sample.csv"))
```

```
## Rows: 32906 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): application_number
## dbl  (2): ego_examiner_id, alter_examiner_id
## date (1): advice_date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
applications
```

```
## # A tibble: 2,018,477 x 16
##    application_number filing_date examiner_name_last examiner_name_first
##    <chr>              <date>      <chr>              <chr>
##  1 08284457           2000-01-26  HOWARD             JACQUELINE
##  2 08413193           2000-10-11  YILDIRIM           BEKIR
##  3 08531853           2000-05-17  HAMILTON           CYNTHIA
##  4 08637752           2001-07-20  MOSHER             MARY
##  5 08682726           2000-04-10  BARR               MICHAEL
##  6 08687412           2000-04-28  GRAY               LINDA
##  7 08716371           2004-01-26  MCMILLIAN          KARA
##  8 08765941           2000-06-23  FORD               VANESSA
##  9 08776818           2000-02-04  STRZELECKA         TERESA
## 10 08809677           2002-02-20  KIM                SUN
## # ... with 2,018,467 more rows, and 12 more variables:
## #   examiner_name_middle <chr>, examiner_id <dbl>, examiner_art_unit <dbl>,
## #   uspc_class <chr>, uspc_subclass <chr>, patent_number <chr>,
## #   patent_issue_date <date>, abandon_date <date>, disposal_type <chr>,
## #   appl_status_code <dbl>, appl_status_date <chr>, tc <dbl>
```

```r
edges
```

```
## # A tibble: 32,906 x 4
##    application_number advice_date ego_examiner_id alter_examiner_id
##    <chr>              <date>                <dbl>             <dbl>
##  1 09402488           2008-11-17            84356             66266
##  2 09402488           2008-11-17            84356             63519
##  3 09402488           2008-11-17            84356             98531
##  4 09445135           2008-08-21            92953             71313
##  5 09445135           2008-08-21            92953             93865
##  6 09445135           2008-08-21            92953             91818
##  7 09479304           2008-12-15            61767             69277
##  8 09479304           2008-12-15            61767             92446
##  9 09479304           2008-12-15            61767             66805
## 10 09479304           2008-12-15            61767             70919
## # ... with 32,896 more rows
```

Question 1

Get gender for examiners

We'll get gender based on the first name of the examiner, which is recorded in the field `examiner_name_first`. We'll use library `gender` for that, relying on a modified version of their own example.

Note that there are over 2 million records in the applications table – that's because there are many records for each examiner, as many as the number of applications that examiner worked on during this time frame. Our first step therefore is to get all *unique* names in a separate list `examiner_names`. We will then guess gender for each one and will join this table back to the original dataset. So, let's get names without repetition:

```r
# install_genderdata_package() # only run this line the first time you use the package, to get data for

# get a list of first names without repetitions
examiner_names <- applications %>%
  distinct(examiner_name_first)

examiner_names
```

```
## # A tibble: 2,595 x 1
##    examiner_name_first
##    <chr>
##  1 JACQUELINE
##  2 BEKIR
##  3 CYNTHIA
##  4 MARY
##  5 MICHAEL
##  6 LINDA
##  7 KARA
##  8 VANESSA
##  9 TERESA
## 10 SUN
## # ... with 2,585 more rows
```

Now let's use function `gender()` as shown in the example for the package to attach a gender and probability to each name and put the results into the table `examiner_names_gender`

```
# get a table of names and gender
examiner_names_gender <- examiner_names %>%
  do(results = gender(.$examiner_name_first, method = "ssa")) %>%
  unnest(cols = c(results), keep_empty = TRUE) %>%
  select(
    examiner_name_first = name,
    gender,
    proportion_female
  )

examiner_names_gender
```

```
## # A tibble: 1,822 x 3
##    examiner_name_first gender proportion_female
##    <chr>               <chr>              <dbl>
##  1 AARON               male              0.0082
##  2 ABDEL               male              0
##  3 ABDOU               male              0
##  4 ABDUL               male              0
##  5 ABDULHAKIM          male              0
##  6 ABDULLAH            male              0
##  7 ABDULLAHI           male              0
##  8 ABIGAIL             female            0.998
##  9 ABIMBOLA            female            0.944
## 10 ABRAHAM             male              0.0031
## # ... with 1,812 more rows
```

Finally, let's join that table back to our original applications data and discard the temporary tables we have just created to reduce clutter in our environment.

```
# remove extra colums from the gender table
examiner_names_gender <- examiner_names_gender %>%
  select(examiner_name_first, gender)

# joining gender back to the dataset
applications <- applications %>%
  left_join(examiner_names_gender, by = "examiner_name_first")

# cleaning up
rm(examiner_names)
rm(examiner_names_gender)
gc()
```

```
##            used  (Mb) gc trigger  (Mb) max used  (Mb)
## Ncells  4752052 253.8    8320468 444.4  5177110 276.5
## Vcells 49958911 381.2   93200558 711.1 80274432 612.5
```

Guess the examiner's race

We'll now use package `wru` to estimate likely race of an examiner. Just like with gender, we'll get a list of unique names first, only now we are using surnames.

```r
examiner_surnames <- applications %>%
  select(surname = examiner_name_last) %>%
  distinct()

examiner_surnames
```

```
## # A tibble: 3,806 x 1
##    surname
##    <chr>
##  1 HOWARD
##  2 YILDIRIM
##  3 HAMILTON
##  4 MOSHER
##  5 BARR
##  6 GRAY
##  7 MCMILLIAN
##  8 FORD
##  9 STRZELECKA
## 10 KIM
## # ... with 3,796 more rows
```

We'll follow the instructions for the package outlined here https://github.com/kosukeimai/wru.

```r
examiner_race <- predict_race(voter.file = examiner_surnames, surname.only = T) %>%
  as_tibble()
```

```
## [1] "Proceeding with surname-only predictions..."
```

```
## Warning in merge_surnames(voter.file): Probabilities were imputed for 698
## surnames that could not be matched to Census list.
```

```r
examiner_race
```

```
## # A tibble: 3,806 x 6
##    surname    pred.whi pred.bla pred.his pred.asi pred.oth
##    <chr>         <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
##  1 HOWARD       0.643   0.295    0.0237   0.005     0.0333
##  2 YILDIRIM     0.861   0.0271   0.0609   0.0135    0.0372
##  3 HAMILTON     0.702   0.237    0.0245   0.0054    0.0309
##  4 MOSHER       0.947   0.00410  0.0241   0.00640   0.0185
##  5 BARR         0.827   0.117    0.0226   0.00590   0.0271
##  6 GRAY         0.687   0.251    0.0241   0.0054    0.0324
##  7 MCMILLIAN    0.359   0.574    0.0189   0.00260   0.0463
##  8 FORD         0.620   0.32     0.0237   0.0045    0.0313
##  9 STRZELECKA   0.666   0.0853   0.137    0.0797    0.0318
## 10 KIM          0.0252  0.00390  0.00650  0.945     0.0198
## # ... with 3,796 more rows
```

As you can see, we get probabilities across five broad US Census categories: white, black, Hispanic, Asian and other. (Some of you may correctly point out that Hispanic is not a race category in the US Census, but these are the limitations of this package.)

Our final step here is to pick the race category that has the highest probability for each last name and then join the table back to the main applications table. See this example for comparing values across columns: https://www.tidyverse.org/blog/2020/04/dplyr-1-0-0-rowwise/. And this one for `case_when()` function: https://dplyr.tidyverse.org/reference/case_when.html.

```
examiner_race <- examiner_race %>%
  mutate(max_race_p = pmax(pred.asi, pred.bla, pred.his, pred.oth, pred.whi)) %>%
  mutate(race = case_when(
    max_race_p == pred.asi ~ "Asian",
    max_race_p == pred.bla ~ "black",
    max_race_p == pred.his ~ "Hispanic",
    max_race_p == pred.oth ~ "other",
    max_race_p == pred.whi ~ "white",
    TRUE ~ NA_character_
  ))

examiner_race
```

```
## # A tibble: 3,806 x 8
##    surname    pred.whi pred.bla pred.his pred.asi pred.oth max_race_p race
##    <chr>         <dbl>    <dbl>    <dbl>    <dbl>    <dbl>      <dbl> <chr>
##  1 HOWARD       0.643   0.295    0.0237   0.005     0.0333      0.643 white
##  2 YILDIRIM     0.861   0.0271   0.0609   0.0135    0.0372      0.861 white
##  3 HAMILTON     0.702   0.237    0.0245   0.0054    0.0309      0.702 white
##  4 MOSHER       0.947   0.00410  0.0241   0.00640   0.0185      0.947 white
##  5 BARR         0.827   0.117    0.0226   0.00590   0.0271      0.827 white
##  6 GRAY         0.687   0.251    0.0241   0.0054    0.0324      0.687 white
##  7 MCMILLIAN    0.359   0.574    0.0189   0.00260   0.0463      0.574 black
##  8 FORD         0.620   0.32     0.0237   0.0045    0.0313      0.620 white
##  9 STRZELECKA   0.666   0.0853   0.137    0.0797    0.0318      0.666 white
## 10 KIM          0.0252  0.00390  0.00650  0.945     0.0198      0.945 Asian
## # ... with 3,796 more rows
```

Let's join the data back to the applications table.

```
# removing extra columns
examiner_race <- examiner_race %>%
  select(surname,race)

applications <- applications %>%
  left_join(examiner_race, by = c("examiner_name_last" = "surname"))

rm(examiner_race)
rm(examiner_surnames)
gc()
```

```
##            used  (Mb) gc trigger  (Mb) max used  (Mb)
## Ncells  5091281 272.0    8320468 444.4  6109947 326.4
## Vcells 53643638 409.3   93200558 711.1 92639527 706.8
```

Examiner's tenure

To figure out the timespan for which we observe each examiner in the applications data, let's find the first and the last observed date for each examiner. We'll first get examiner IDs and application dates in a separate table, for ease of manipulation. We'll keep examiner ID (the field `examiner_id`), and earliest and latest dates for each application (`filing_date` and `appl_status_date` respectively). We'll use functions in package `lubridate` to work with date and time values.

```
examiner_dates <- applications %>%
  select(examiner_id, filing_date, appl_status_date)

examiner_dates
```

```
## # A tibble: 2,018,477 x 3
##    examiner_id filing_date appl_status_date
##          <dbl> <date>      <chr>
##  1       96082 2000-01-26  30jan2003 00:00:00
##  2       87678 2000-10-11  27sep2010 00:00:00
##  3       63213 2000-05-17  30mar2009 00:00:00
##  4       73788 2001-07-20  07sep2009 00:00:00
##  5       77294 2000-04-10  19apr2001 00:00:00
##  6       68606 2000-04-28  16jul2001 00:00:00
##  7       89557 2004-01-26  15may2017 00:00:00
##  8       97543 2000-06-23  03apr2002 00:00:00
##  9       98714 2000-02-04  27nov2002 00:00:00
## 10       65530 2002-02-20  23mar2009 00:00:00
## # ... with 2,018,467 more rows
```

The dates look inconsistent in terms of formatting. Let's make them consistent. We'll create new variables `start_date` and `end_date`.

```
examiner_dates <- examiner_dates %>%
  mutate(start_date = ymd(filing_date), end_date = as_date(dmy_hms(appl_status_date)))
```

Let's now identify the earliest and the latest date for each examiner and calculate the difference in days, which is their tenure in the organization.

```
examiner_dates <- examiner_dates %>%
  group_by(examiner_id) %>%
  summarise(
    earliest_date = min(start_date, na.rm = TRUE),
    latest_date = max(end_date, na.rm = TRUE),
    tenure_days = interval(earliest_date, latest_date) %/% days(1)
    ) %>%
  filter(year(latest_date)<2018)

examiner_dates
```

```
## # A tibble: 5,625 x 4
##    examiner_id earliest_date latest_date tenure_days
##          <dbl> <date>        <date>            <dbl>
##  1       59012 2004-07-28    2015-07-24         4013
##  2       59025 2009-10-26    2017-05-18         2761
##  3       59030 2005-12-12    2017-05-22         4179
##  4       59040 2007-09-11    2017-05-23         3542
##  5       59052 2001-08-21    2007-02-28         2017
```

```
##  6       59054 2000-11-10    2016-12-23         5887
##  7       59055 2004-11-02    2007-12-26         1149
##  8       59056 2000-03-24    2017-05-22         6268
##  9       59074 2000-01-31    2017-03-17         6255
## 10       59081 2011-04-21    2017-05-19         2220
## # ... with 5,615 more rows
```

Joining back to the applications data.

```
applications <- applications %>%
  left_join(examiner_dates, by = "examiner_id")

rm(examiner_dates)
gc()
```

```
##            used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells  5105019 272.7   15041074  803.3  15041074  803.3
## Vcells 66021822 503.8  134384802 1025.3 134253203 1024.3
```

Question2

```
# we pick work group 163 and 172

w164 <- subset(applications, grepl("^164", applications$examiner_art_unit))
w164$gender <- factor(w164$gender)
w164$race <- factor(w164$race)
w241 <- subset(applications, grepl("^241", applications$examiner_art_unit))
w241$gender <- factor(w241$gender)
w241$race <- factor(w241$race)

# summary for group 164
summary(w164$gender)
```

```
## female   male   NA's
##  41398  38393  13551
```

```
summary(w164$race)
```

```
##    Asian    black Hispanic    white
##    21651     3899     1117    66675
```

```
summary(w164$tenure_days)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##     314    6074    6315    6128    6338    6350    1884
```

```
# summry for group 241
summary(w241$gender)
```

```
## female   male   NA's
##   2781  13256   3554
```

```
summary(w241$race)
```

```
##    Asian    black Hispanic    white
##    10117      848      381     8245
```

```
summary(w241$tenure_days)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##     548    4147    5257    4688    5911    6335      75
```

Race and gender distribution for work group 164 and 241 respectively

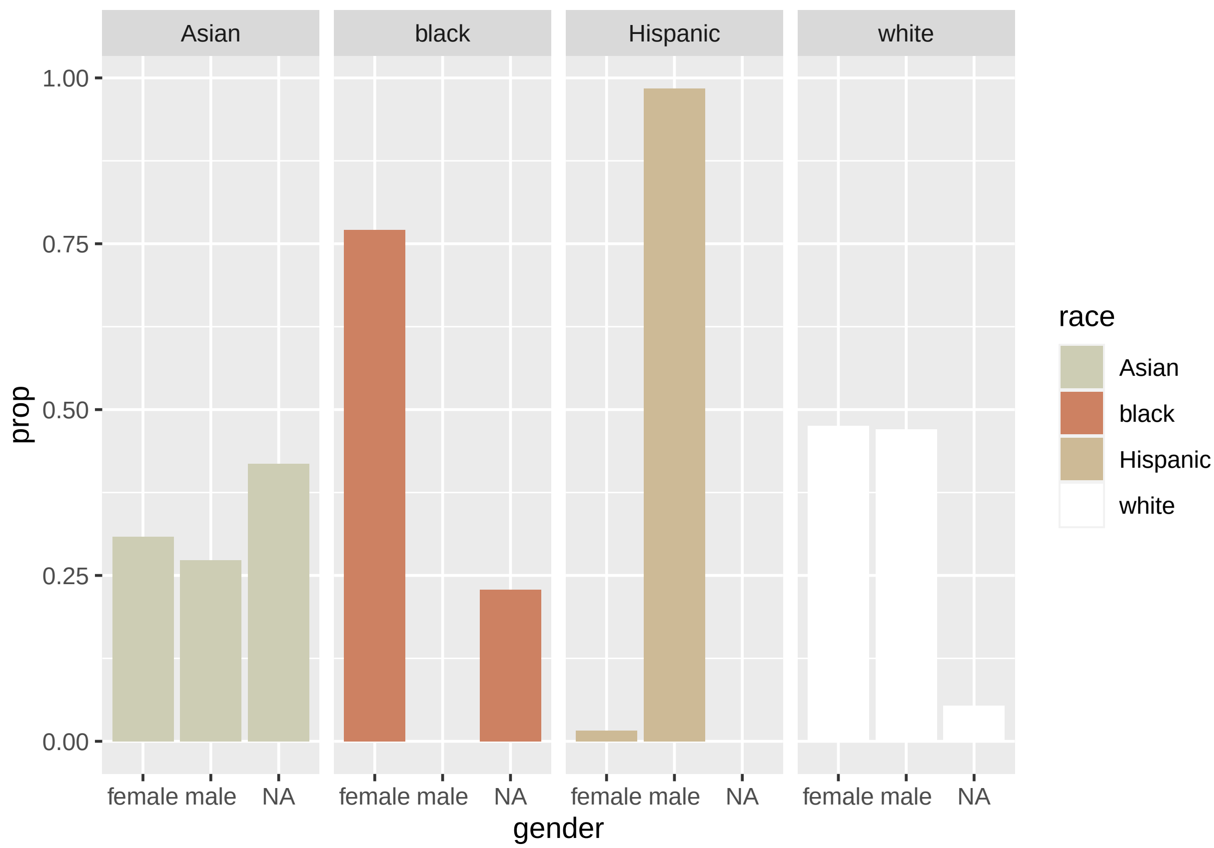
```
# merge
w164$workgroup <- c('164')
w241$workgroup <- c('241')

merged = union(x = w164,y = w241)
```

Gender distribution in races for work group 164

```
toPlot<-w164%>%
  group_by(gender, race)%>%
  summarise(n = n())%>%
  group_by(race)%>%
  mutate(prop = n/sum(n))
```

```
## `summarise()` has grouped output by 'gender'. You can override using the
## `.groups` argument.
```

```
ggplot(data = toPlot, aes(gender, prop, fill = race)) +
  geom_col() +
  facet_grid(~race)+
  scale_fill_manual(values = c("lightyellow3","lightsalmon3", "wheat3","white"))
```

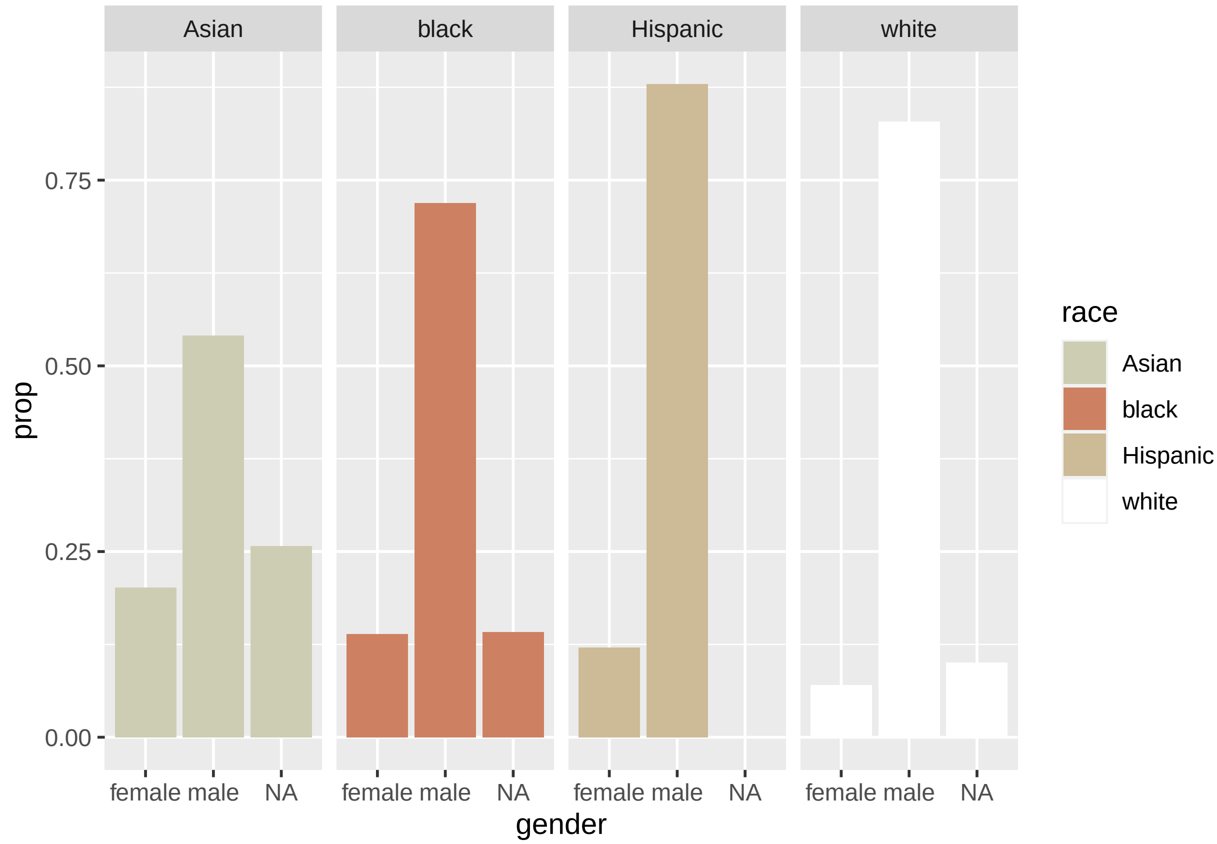


Gender distribution in races for work group 241

```
toPlot<-w241 %>%
  group_by(gender, race)%>%
  summarise(n = n())%>%
  group_by(race)%>%
  mutate(prop = n/sum(n))
```

```
## `summarise()` has grouped output by 'gender'. You can override using the
## `.groups` argument.
```

```
ggplot(data = toPlot, aes(gender, prop, fill = race)) +
  geom_col() +
  facet_grid(~race)+
  scale_fill_manual(values = c("lightyellow3","lightsalmon3", "wheat3","white"))
```



Question 3

Create node lists for eacch work group

```
# join selected work groups with edges list
edges <- drop_na(edges, ego_examiner_id)
edges <-drop_na(edges, alter_examiner_id)
w164_2 <- inner_join(w164, edges, by = "application_number", copy = FALSE)
w241_2 <- inner_join(w241, edges, by = "application_number", copy = FALSE)

# nodes dataframe of work groups and merge them
w164_nodes1 <- w164_2 %>%
  distinct(ego_examiner_id) %>%
  rename(ID = ego_examiner_id)

w164_nodes2 <- w164_2 %>%
  distinct(alter_examiner_id) %>%
  rename(ID = alter_examiner_id)

w241_nodes1 <- w241_2 %>%
  distinct(ego_examiner_id) %>%
  rename(ID = ego_examiner_id)

w241_nodes2 <- w241_2 %>%
  distinct(alter_examiner_id) %>%
```

```r
  rename(ID = alter_examiner_id)

# merge the two dataframes for each work goup
w164_nodes <- union_all(w164_nodes1, w164_nodes2)
w241_nodes <- union_all(w241_nodes1, w241_nodes2)

w164_nodes <- unique(w164_nodes)
w241_nodes <- unique(w241_nodes)

head(w164_nodes, 5)
```

```
## # A tibble: 5 x 1
##      ID
##   <dbl>
## 1 91688
## 2 97910
## 3 75775
## 4 70204
## 5 71120
```

Create final edge list

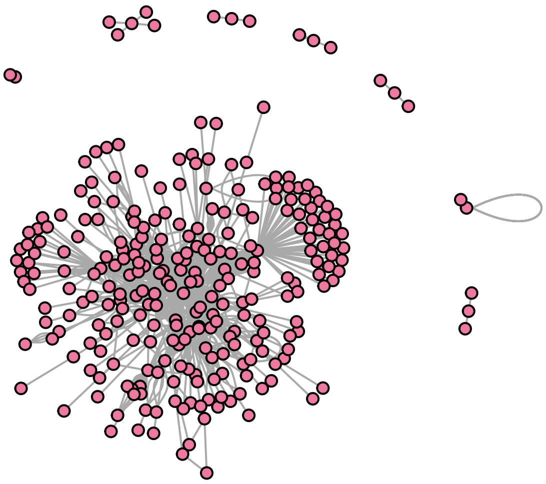
```r
w164_edges <- w164_2 %>%
  select(ego_examiner_id, alter_examiner_id)

w241_edges <- w241_2 %>%
  select(ego_examiner_id, alter_examiner_id)

head(w164_edges, 5)
```

```
## # A tibble: 5 x 2
##   ego_examiner_id alter_examiner_id
##             <dbl>             <dbl>
## 1           91688             71059
## 2           91688             67669
## 3           97910             59738
## 4           97910             99004
## 5           97910             67669
```

```r
g_w164 <- graph_from_data_frame(w164_edges, directed=FALSE)
g_w241 <- graph_from_data_frame(w241_edges, directed=FALSE)
```

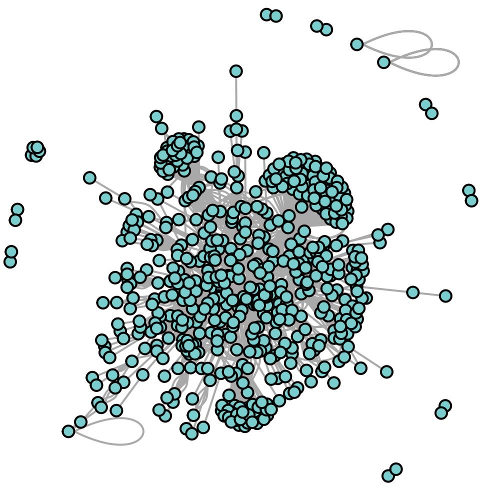
Plot vertex graph for work group 164

```r
plot(g_w164, layout=layout.fruchterman.reingold,
    vertex.size = 5,
    vertex.label = NA,
    vertex.color = "palevioletred2")
```



Plot vertex graph for work group 241

```
plot(g_w241, layout=layout.fruchterman.reingold,
    vertex.size = 5,
    vertex.label = NA,
    vertex.color = "darkslategray3")
```



Calculate centralities

```
# betweenness
bc_w164 <- sort(betweenness(g_w164), decreasing = TRUE)
bc_w241 <- sort(betweenness(g_w241), decreasing = TRUE)

# degree
dg_w164 <- sort(degree(g_w164), decreasing = TRUE)
dg_w241 <- sort(degree(g_w241), decreasing = TRUE)

# closeness
cc_w164 <- sort(closeness(g_w164), decreasing = TRUE)
cc_w241 <- sort(closeness(g_w241), decreasing = TRUE)

print("top 5 of betwenness centrality for work group 164")
```

```
## [1] "top 5 of betwenness centrality for work group 164"
```

```
print(head(bc_w164,5))
```

```
##     72882     87897     97910     66266     73260
## 12338.868  9951.339  6984.072  4250.095  3709.533
```

```
print("top 5 of betwenness centrality for work group 241")
```

```
## [1] "top 5 of betwenness centrality for work group 241"
```

```r
print(head(bc_w241,5))
```

```
##    62919    62038    91499    95183    61485
## 67440.85 21071.27 16727.50 15711.58 15142.94
```

```r
print("top 5 of degree centrality for work group 164")
```

```
## [1] "top 5 of degree centrality for work group 164"
```

```r
print(head(dg_w164,5))
```

```
## 97910 72882 87897 59738 99004
##   170   154    96    83    82
```

```r
print("top 5 of degree centrality for work group 241")
```

```
## [1] "top 5 of degree centrality for work group 241"
```

```r
print(head(dg_w241,5))
```

```
## 62919 67226 92078 61485 71764
##   178   175   132   101   100
```

```r
print("top 5 of closeness centrality for work group 164")
```

```
## [1] "top 5 of closeness centrality for work group 164"
```

```r
print(head(cc_w164,15))
```

```
##     97706     76749     75119     67435     84944     59658     80908     67013
## 1.0000000 1.0000000 1.0000000 1.0000000 0.5000000 0.5000000 0.5000000 0.5000000
##     97072     86403     68637     97834     95085     62142     70907
## 0.3333333 0.3333333 0.3333333 0.3333333 0.3333333 0.3333333 0.3333333
```

```r
print("top 5 of closeness centrality for work group 241")
```

```
## [1] "top 5 of closeness centrality for work group 241"
```

```r
print(head(cc_w241,15))
```

```
## 91652 93841 66060 97883 63765 72734 70399 61007 66905 96538 64053 97508 75981
##     1     1     1     1     1     1     1     1     1     1     1     1     1
## 63155 72089
##     1     1
```

Pick measures of centrality

I would pick betweenness centrality and degree centrality from the three centralities I calculated above, because in the USPTO case: (1) how many contacts does one examiner have (degree centrality) is a useful information, and (2) the transfer of information among all examiners are important, making the examiner who on the shortest paths between other examiners more important. Additionally, because for work group 241, there are many examiners who are of the highest closeness centrality, the advantage of having the highest closeness centrality is not very strong in my specific case.